Spatiotemporal variation in vegetation net primary productivity and its relationship with meteorological factors in the Tarim River Basin of China from 2001 to 2020 based on the Google Earth Engine

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Abstract: Vegetation growth status is an important indicator of ecological security. The Tarim River Basin is located in the inland arid region of Northwest China and has a highly fragile ecological environment. Assessing the vegetation net primary productivity (NPP) of the Tarim River Basin can provide insights into the vegetation growth variations in the region. Therefore, based on the Google Earth Engine (GEE) cloud platform, we studied the spatiotemporal variation of vegetation NPP in the Tarim River Basin (except for the eastern Gobi and Kumutag deserts) from 2001 to 2020 and analyzed the correlations between vegetation NPP and meteorological factors (air temperature and precipitation) using the Sen slope estimation method, coefficient of variation, and rescaled range analysis method. In terms of temporal characteristics, vegetation NPP in the Tarim River Basin showed an overall fluctuating upward trend from 2001 to 2020, with the smallest value of 118.99 g C/(m^2•a) in 2001 and the largest value of 155.07 g C/(m^2•a) in 2017. Regarding the spatial characteristics, vegetation NPP in the Tarim River Basin showed a downward trend from northwest to southeast along the outer edge of the study area. The annual average value of vegetation NPP was 133.35 g C/(m^2•a), and the area with annual average vegetation NPP values greater than 100.00 g C/(m^2•a) was 82,638.75 km^2, accounting for 57.76% of the basin. The future trend of vegetation NPP was dominated by anti-continuity characteristic; the percentage of the area with anti-continuity characteristic was 63.57%. The area with a significant positive correlation between vegetation NPP and air temperature accounted for 53.74% of the regions that passed the significance test, while the area with a significant positive correlation between vegetation NPP and precipitation occupied 98.68% of the regions that passed the significance test. Hence, the effect of precipitation on vegetation NPP was greater than that of air temperature. The results of this study improve the understanding on the spatiotemporal variation of vegetation NPP in the Tarim River Basin and the impact of meteorological factors on vegetation NPP.

Keywords: vegetation net primary productivity (NPP); air temperature; precipitation; Hurst index; Google Earth Engine; Tarim River Basin

Citation: CHEN Limei, Abudureheman HALIKE, YAO Kaixuan, WEI Qianqian. 2022. Spatiotemporal variation in vegetation net primary productivity and its relationship with meteorological factors in the Tarim River Basin of China from 2001 to 2020 based on the Google Earth Engine. Journal of Arid Land, 14(12): 1377–1394. https://doi.org/10.1007/s40333-022-0075-z

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Received 2022-02-28; revised 2022-09-18; accepted 2022-10-05

1 Introduction

Net primary productivity (NPP) is the total amount of organic matter produced by green plants under photosynthesis minus the organic matter consumed by autotrophic respiration (Bondeau et al., 1999; Choudhury, 2000; Piao et al., 2003; Turner et al., 2006; Jassal et al., 2007; Jiao et al., 2018). Vegetation NPP is the result of the combined action of the physiological characteristics of vegetation and the external environment, which can reflect the quality of the terrestrial ecosystem (Gao, 2019; Zhang et al., 2021) and the productivity of surface vegetation under natural environmental conditions, and is an important determining factor of regional ecological support capacity (Michaletz et al., 2014; Pan et al., 2018). NPP is also an important indicator of the growth status of vegetation and a critical indicator of ecological security. Thus, assessing vegetation NPP provides insights into the health and integrity of the ecosystem. Therefore, the study of the global or regional spatiotemporal characteristics of vegetation NPP can be used to evaluate the health and stability of the ecosystem and address ecological and environmental challenges (Guo et al., 2017; Zhao et al., 2020).

There are relatively few studies focusing on the long-term spatiotemporal variation of vegetation NPP and its relationship with meteorological factors in the Tarim River Basin of Xinjiang Uygur Autonomous Region, China; however, previous studies have explored vegetation NPP in the western arid regions of China (Zhang, 2021). For example, Zhang et al. (2018) used the Thornthwaite Memorial Model to estimate vegetation NPP in the Shiyang River Basin of China and found that variations in vegetation NPP in the Shiyang River Basin are primarily increasing and precipitation is the main influencing factor of vegetation NPP. Bai et al. (2015) used the measured herbaceous NPP and water burial depth data from the lower reaches of the Tarim River to establish a relationship model, and determined that herbaceous NPP in the lower reaches of the Tarim River shows a decreasing trend correlated with the increase in groundwater burial depth. Cui et al. (2020) recently estimated vegetation NPP of the Tarim River Basin in the growing season from 2006 to 2016 using an improved Carnegie-Ames-Stanford approach (CASA) model and showed that vegetation NPP of the Tarim River Basin in the growing season has a fluctuating increasing trend, whereas the spatial distribution exhibits a decreasing trend from northwest to southeast. Additionally, Zhao et al. (2019) used MOD17A3 remote sensing data to analyze the spatiotemporal variation of vegetation NPP in the Bortala-Jinghe River Basin in Xinjiang from 2000 to 2015 and found that vegetation NPP is high in the middle of the basin but low in the surrounding areas, with precipitation being the most influencing factor. In the existing research on vegetation NPP in arid and semi-arid regions, NPP data have mainly been obtained from NPP estimation models, NPP measured data, and existing data products. Although these data acquisition methods are reliable, they are relatively common. The process of data acquisition and preprocessing can be complex and time-consuming.

The Google Earth Engine (GEE) is a remote sensing big data analysis platform that was launched in 2010 based on the Google Cloud Service infrastructure and is dedicated to geographical data processing and analysis (Gorelick et al., 2017; Amani et al., 2020; Wang et al., 2020). This platform stores massive multisource data publicly available from many organizations (Gorelick et al., 2017; Zhang et al., 2021), with technical advantages such as excellent cloud computing, standardized user interfaces, good development ecology, and free service platform. Using literature reviews, Gorelick et al. (2017), Kumar and Mutanga (2018), Mutanga and Kumar (2019), Amani et al. (2020), and Tamiminia et al. (2020) assessed the GEE, focusing on the birth, applications, trends, and potential uses of the GEE.

Currently, the GEE is used in a wide range of research fields (Lobell et al., 2015; Dong et al., 2016; Pekel et al., 2016; Huang et al., 2017), including forest ecosystem change, food security, disaster early warning system, water resources management, climate change, environmental protection, and vegetation dynamics. Yin et al. (2020) used the GEE to analyze the spatiotemporal patterns of global forest NPP from 2004 to 2013 as well as their relationships with various influencing factors, observing that climate has a large influence on forest NPP and the patterns of

climate oscillations are synchronized with forest growth conditions to some extent. Additionally, Li and He (2022) used the GEE to quantitatively explore vegetation NPP changes and their mechanisms under different drought stress conditions in Central Asia from 1990 to 2020 and found that the effect of land cover change on vegetation NPP in Central Asia is higher than that of climate change. Moreover, Zhang et al. (2021) studied the spatiotemporal characteristics of vegetation NPP on the Tibetan Plateau from 2001 to 2017 based on the GEE and discussed the effects of climate change, altitude, and human activities on vegetation NPP in the Tibetan Plateau. Based on the GEE, Gu et al. (2021) analyzed the spatiotemporal variation in vegetation NPP in the Greater Mekong Subregion from 2001 to 2019 and found that the overall vegetation NPP trend in the Greater Mekong Subregion is insignificant, and it is significantly negatively correlated with annual average air temperature, showing a spatial heterogeneity pattern. For the Tarim River Basin, there have been limited studies on vegetation NPP based on the GEE, and data on vegetation NPP on the basis of this platform are also lacking.

Therefore, in this study, we used the GEE and analyzed the relationship between vegetation NPP and key factors to provide insights into the changes of vegetation NPP in the Tarim River Basin. Vegetation NPP data were preprocessed on the GEE and can be used immediately after downloading, which shortens the data processing time, improves the efficiency of data processing, and is more convenient and faster than other NPP data acquisition methods. Prior research on vegetation NPP in the Tarim River Basin has mainly been undertaken on grassland NPP but not on vegetation NPP in the whole basin (Gu et al., 2021). The Tarim River Basin is located in an arid area and dominated by desert and bare desert substrates, where vegetation plays an important role in water conservation. The ecological environment of the Tarim River Basin is highly fragile; hence, the growth and changes in vegetation have been closely monitored. Evaluating the spatiotemporal variation in vegetation NPP in the Tarim River Basin and analyzing the influence of meteorological factors on vegetation NPP are important for understanding the characteristics of the carbon cycle in the basin. The findings can also inform the protection and sustainable utilization of vegetation resources, determine the effectiveness of construction projects such as reforestation and holistic watershed management, and provide a basis for the formulation of ecological construction and sustainable development strategies in the basin.

2 Materials and methods

2.1 Study area

The Tarim River Basin is in the southern part of Xinjiang Uygur Autonomous Region in China, between 71°39′–93°45′E and 34°20′–43°39′N. The basin sits between the Tianshan Mountains and Kunlun Mountains, with a length of 1100 km from east to west, a width of 600 km from north to south, and a total basin area of 1.028×10^{6} km^{2}. It is the largest inland river basin in the world (Chu et al., 2021), consisting of the Kashgar River Basin, Yarkant River Basin, Hotan River Basin, Kriya River Basin, Cherchen River Basin, Kaikong River Basin, Weigan River Basin, Aksu River Basin, Tarim River main stream Basin, and Taklimakan, eastern Gobi, and Kumutag deserts (Fig. 1). As the eastern Gobi and Kumutag deserts are largely devoid of vegetation growth in all seasons, these two regions were removed from the study during the computational analysis.

2.2 Data sources

Remote sensing data were derived from MOD17A3HGF NPP and Landsat 8 NDVI data provided by the GEE, with time series of year-by-year data from 2001 to 2020. The spatial resolution of NPP data is 500 m and the temporal resolution is 1 a. Air temperature and precipitation data were obtained from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn/), with a time series of 2001–2020 and a spatial resolution of 1000 m. To maintain consistency with the spatial resolution of NPP data, we resampled the spatial resolution of meteorological data to 500 m and the temporal resolution to 1 month. Air temperature data were selected for the growing season (April–October) of each year.

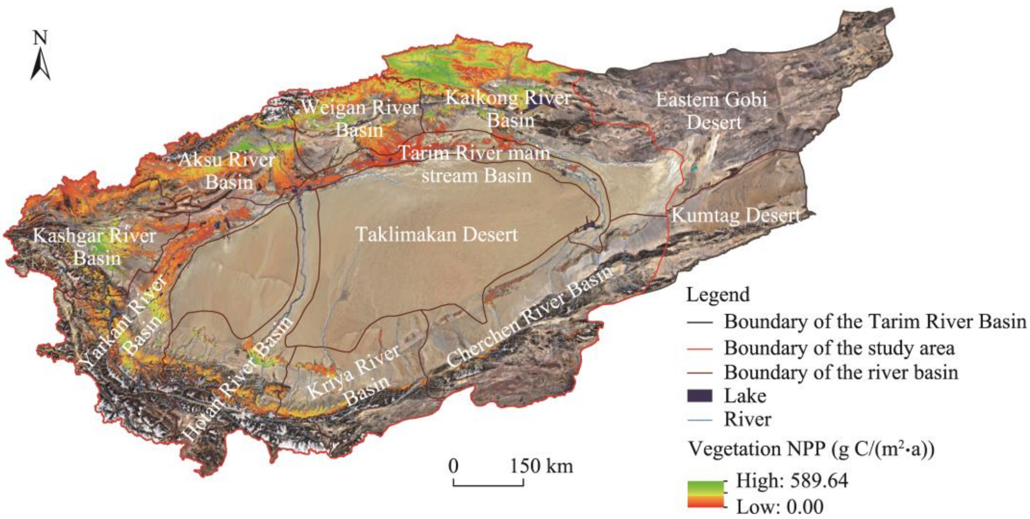

Fig. 1 Overview of the Tarim River Basin and spatial distribution of vegetation net primary productivity (NPP) in the study area. Note that as the eastern Gobi and Kumutag deserts are largely devoid of vegetation growth in all seasons, these two regions were removed from the study during the computational analysis.

2.3 Methods

2.3.1 Trend analysis of vegetation NPP change

The Sen slope estimation method is often used to assess linear relationships (Sen, 1968) and has been applied in several previous studies (e.g., Zhao et al., 2017; Dawood et al., 2018). Compared with the linear regression analysis, the Sen slope estimation method is not affected by the total data error or outliers and can effectively reduce the interference of noise (Wang et al., 2021). The calculation formula is as follows (Wang et al., 2015; Cao et al., 2018):

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i, \tag{1}$$

where β is the Sen slope; x_j and x_i are the time series data; and i and j are the time series attribute values ($i \neq j$). β greater than zero indicates that the time series is in an upward trend, whereas β lower than zero indicates that the time series is in a downward trend. To verify the accuracy of the calculation results, we combined the Sen slope estimation method and Mann-Kendall test to complete the slope calculation results (Kendall, 1948).

For a time series X_i (i=1, 2, …, i, …, j, …, n), the standardized test statistic Z can be calculated using the following equations:

$$Z = \begin{cases} \dfrac{S}{\sqrt{Var(S)}} & (S > 0) \\ 0 & (S = 0) \\ \dfrac{S+1}{\sqrt{Var(S)}} & (S < 0) \end{cases}, \tag{2}$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i), \tag{3}$$

$$sign(\theta) \begin{cases} 1 \ (\theta > 0) \\ 0 \ (\theta = 0) \\ -1 \ (\theta < 0) \end{cases}, \tag{4}$$

$$E(S)=0\,, \tag{5}$$

$$Var(S)=\frac{n(n-1)(2n+5)}{18}\,, \tag{6}$$

where $Var(S)$ is the variance of the accumulated number S; *sign* is the sign function; n is the number of data; θ is the difference of x_j and x_i (θ=x_j–x_i); and $E(S)$ is the mean of the accumulated number S. When n≥8, the standardized test statistic Z is approximately normally distributed.

The rate of change indicates the percentage change of vegetation NPP. The calculation formula is as follows:

$$\mathrm{NPP}_c=\frac{\beta}{\overline{\mathrm{NPP}}}\times n\times 100\%\,, \tag{7}$$

where NPP_c is the rate of change in vegetation NPP(g C/(m^2•a)); and $\overline{\mathrm{NPP}}$ is the average NPP for n years (g C/(m^2•a)), where n is the number of data (years).

2.3.2 Stability analysis of vegetation NPP

Coefficient of variation (CV), also known as coefficient of stability, was used to characterize the volatility of vegetation NPP and the stability of the time series. The CV for each raster vegetation NPP in the Tarim River Basin from 2001 to 2020 was calculated, and the results were further analyzed. The larger the calculated result, the greater the fluctuation and instability of vegetation NPP with time. The calculation formula is as follows (Huang, 2020):

$$\mathrm{CV}=\frac{\sigma}{\mu}\,, \tag{8}$$

where σ is the standard deviation; and μ is the arithmetic mean.

2.3.3 Analysis of the future trend of vegetation NPP change

The Hurst index, which is calculated based on the rescaled range analysis method, was proposed to characterize the persistence characteristics of vegetation NPP (Dai et al., 2010; Li et al., 2012; Yuan et al., 2013; Tong et al., 2018). The Hurst index can better distinguish the autocorrelation of the time series data; hence, it is often used in the study of vegetation cover change. The size of the Hurst index can be used to evaluate the persistence of the time series data, where the Hurst index is between 0.0 and 1.0. If 0.0<Hurst index<0.5, it indicates that the time series is anti-continuity; that is, the future trend of change is the opposite of the past trend (the closer the Hurst index is to zero, the stronger the time series is anti-continuity). Conversely, if Hurst index=0.5, the time series is random, and there is no long-term correlation between the future trend of change and the past trend. Moreover, if 0.5<Hurst index<1.0, the time series is sustainability; that is, the future trend is consistent with the past trend and has the characteristic of long-term correlation (the closer the Hurst index is to 1.0, the stronger the time series is sustainability) (Zhu, 2019).

The time series is defined as $\xi(t)$ (where t=1, 2, …), the sequence is defined as τ (where τ=1, 2, …), and τ represents the mean series, as follows (Zhu et al., 2011):

$$\langle\xi\rangle_\tau=\frac{1}{\tau}\sum_{t=1}^{\tau}\xi(t),\ \text{where } 1\le t\le\tau\ (t=1,\ 2,\ \ldots)\,. \tag{9}$$

The cumulative deviation ($X(t, \tau)$) at time t is defined as follows:

$$X(t,\tau)=\sum_{u=1}^{t}(\xi(u)-\langle\xi\rangle_\tau),\ \text{where } 1\le t\le\tau\,, \tag{10}$$

where u is the cumulative summation variable.

The polar difference R is defined as follows:

$$R(\tau)=\max X(t,\tau)-\min X(t,\tau),\ \text{where } 1\le t\le\tau\,. \tag{11}$$

The standard deviation S is defined as follows:

$$S(\tau)=\sqrt{\frac{1}{\tau}\sum_{t=1}^{\tau}\left[\xi(t)-\langle\xi\rangle_{\tau}\right]^{2}}\ . \tag{12}$$

R, S, and τ are related as follows:

$$R(\tau)/S(\tau)=\mathrm{c}\times\tau^{H}\ , \tag{13}$$

where $R(\tau)$ is the extreme deviation; $S(\tau)$ is the standard deviation; c is a constant; and H is the Hurst index. The Hurst index (H) is fitted using the least squares method and calculated by Equation 14:

$$\log(R/S)\tau=\log\mathrm{c}+H\times\log(\tau)\ , \tag{14}$$

where log(R/S)τ series is the independent variable; and log(τ) series is the dependent variable.

2.3.4 Correlation analysis of vegetation NPP and meteorological factors

Air temperature and precipitation are the main climatic factors affecting vegetation NPP, and the correlations of vegetation NPP with air temperature and precipitation were analyzed in this study. The partial correlation coefficients of vegetation NPP with air temperature and precipitation were calculated separately, and the correlation coefficients were calculated before calculating the partial correlation coefficients. The calculation formula is as follows:

$$R_{xy}=\frac{\sum_{g=1}^{n}[(x_g-\bar{x})(y_g-\bar{y})]}{\sqrt{\sum_{g=1}^{n}(x_g-\bar{x})^2}\sqrt{\sum_{g=1}^{n}(y_g-\bar{y})^2}}\ , \tag{15}$$

where R_{xy} is the correlation coefficient of the two variables x and y; x_g and y_g are the values of x and y in the g^{th} year, respectively; n is the number of years; $\bar{x}$ is the mean of x values; and $\bar{y}$ is the mean of y values. The more the correlation coefficient tends to 1, the higher the correlation between the variables, whereas the more the correlation coefficient is close to 0, the weaker the correlation between the variables. If the calculated result is higher than zero, the correlation is positive, while if the calculated result is lower than zero, the correlation is negative.

The partial correlation coefficients of vegetation NPP with air temperature and precipitation are calculated as:

$$R_{xy,z}=\frac{R_{xy}-R_{xz}R_{yz}}{\sqrt{(1-R_{xz}{}^{2})}\sqrt{(1-R_{yz}{}^{2})}}\ , \tag{16}$$

where $R_{xy,z}$ is the partial correlation coefficient between the dependent variable x and independent variable y after fixing the independent variable z; R_{xz} is the correlation coefficient of the two variables x and z; and R_{yz} is the correlation coefficient of the two variables y and z. In this study, the dependent variable was vegetation NPP and the independent variables were mean air temperature and precipitation. The significance test of the partial correlation coefficient is generally performed using the t-test:

$$t\text{-test}=\frac{R_{xy,z}}{\sqrt{1-R^{2}{}_{xy,z}}}\sqrt{n-m-1}\ , \tag{17}$$

where m is the number of independent variables (m=2).

As shown in Figure 2, we used the vegetation NPP data of the Tarim River Basin in the GEE, analyzed the spatiotemporal changes of vegetation NPP using the GEE, preprocessed the meteorological data, and analyzed the correlations between vegetation NPP and meteorological factors. The vegetation changes in the Tarim River Basin were obtained to provide deeper insights into vegetation NPP in the Tarim River Basin.

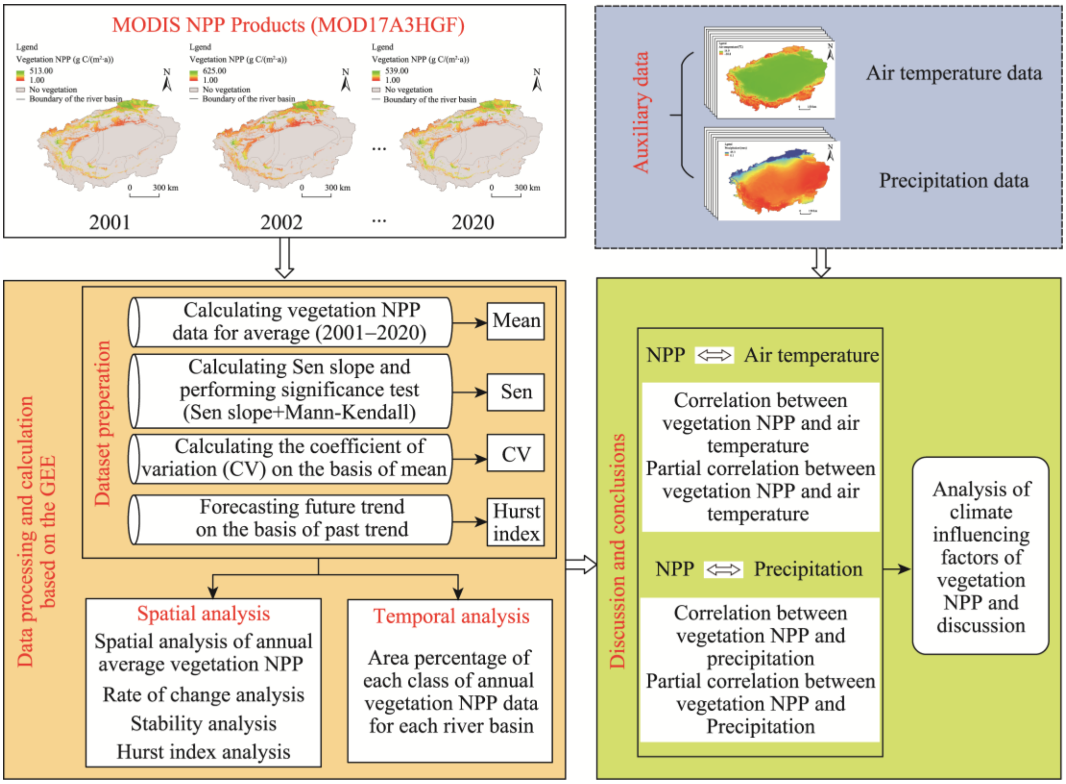

Fig. 2 Flow chart of the spatiotemporal variation in vegetation NPP and its relationship with meteorological factors in the Tarim River Basin. GEE, Google Earth Engine.

3 Results

3.1 Temporal distribution characteristics of annual average vegetation NPP

Statistical analyses on the trend graph of annual average vegetation NPP in the Tarim River Basin (Fig. 3) showed an overall volatility uptrend of annual average vegetation NPP from 2001 to 2020. Specifically, annual average vegetation NPP ranged from 118.99 to 155.07 g C/(m^2•a), with the maximum value of 155.07 g C/(m^2•a) occurring in 2017, the minimum value of 118.99 g C/(m^2•a)

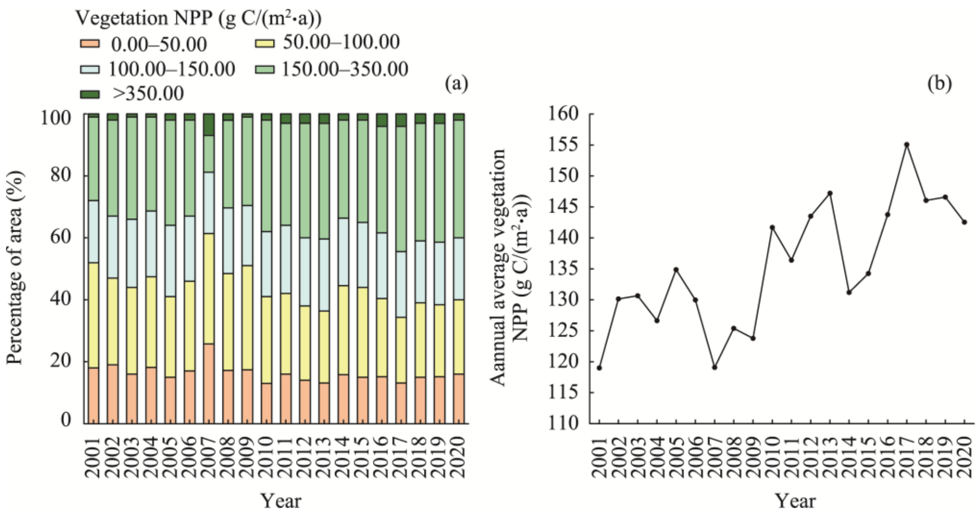

Fig. 3 Percentage of the area occupied by different classes of annual average vegetation NPP (a) and change trend of annual average vegetation NPP (b) in the Tarim River Basin from 2001 to 2020

in 2001, and an average annual vegetation NPP of 135.39 g C/(m^2·a) during 2001–2020. Annual average NPP for each year from 2001 to 2020 was divided into five classes (0.00–50.00, 50.00–100.00, 100.00–150.00, 150.00–350.00, and >350.00 g C/(m^2·a)), and the percentage of the area occupied by each class was further calculated. The percentage of the area occupied by annual average vegetation NPP of 0.00–50.00 g C/(m^2·a) and annual average vegetation NPP of 50.00–100.00 g C/(m^2·a) from 2001 to 2020 showed a fluctuating decreasing trend, the percentage of the area occupied by annual average vegetation NPP of 100.00–150.00 g C/(m^2·a) fluctuated insignificantly, and the percentage of the area occupied by annual average vegetation NPP of 150.00–350.00 g C/(m^2·a) and annual average vegetation NPP of greater than 350.00 g C/(m^2·a) showed a fluctuating increasing trend.

3.2 Spatial distribution and variation of vegetation NPP

3.2.1 Spatial distribution characteristics of annual average vegetation NPP

Annual average vegetation NPP of the Tarim River Basin from 2001 to 2020 showed a more significant spatially divergent pattern (Fig. 4a). The total annual average vegetation NPP in the Tarim River Basin was 76,308,679.00 g C/a, with a mean value of 133.35 g C/(m^2·a), and a maximum value of 589.64 g C/(m^2·a) in the Kashgar River Basin. In the Tarim River Basin, the area with annual average vegetation NPP values greater than 100.00 g C/(m^2·a) was 82,638.75 km^2, accounting for 57.76% of the basin, whereas the area with annual average vegetation NPP values less than 100.00 g C/(m^2·a) was 60,423.25 km^2, accounting for the remaining 42.24% of the basin. In terms of spatial distribution, annual average vegetation NPP in the Tarim River Basin generally decreased from northwest to southeast along the outer edge of the study area. All river basins showed higher average annual vegetation NPP values in the intermountain, pre-mountain alluvial, and oasis zones where the rivers originated. Moreover, average annual vegetation NPP values were lower in the marginal zone of the Taklimakan Desert and the edge of the Tarim River Basin.

To further study the spatial distribution of vegetation NPP in each river basin, we created Figure 4b to analyze the percentage of the area occupied by different classes of annual average vegetation NPP in each river basin. The percentage of the area occupied by annual average vegetation NPP values of less than 100.00 g C/(m^2·a) in the Kashgar River Basin, Cherchen River Basin, and Tarim River main stream Basin exceeded 50.00% of the Tarim River Basin, whereas the percentage of the area occupied by annual average vegetation NPP values of greater than

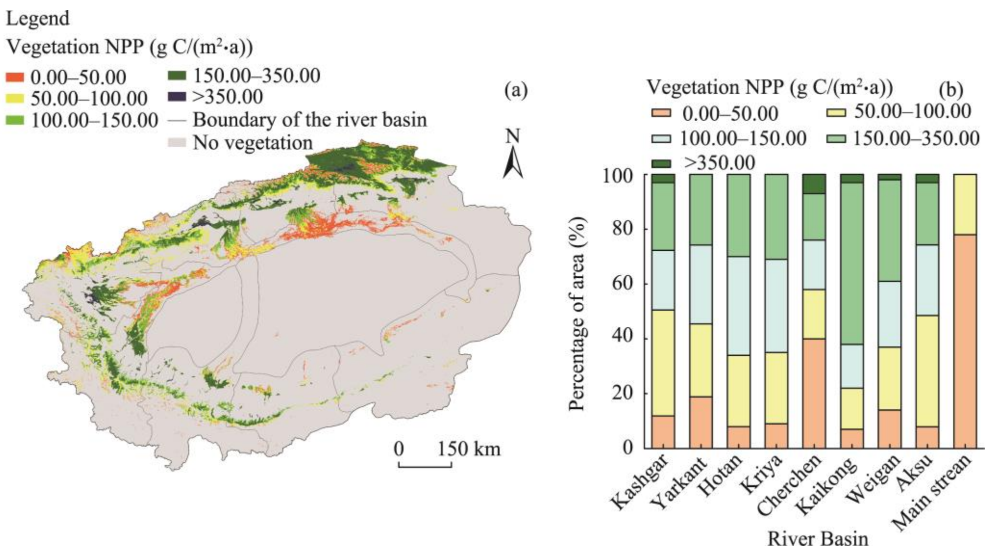

Fig. 4 Spatial distribution of annual average vegetation NPP in the Tarim River Basin (a) and percentage of the area occupied by different classes of annual average vegetation NPP in each river basin (b) during 2001–2020

100.00 g C/(m²•a) in the Yarkand River Basin, Hotan River Basin, Kriya River Basin, Kaikong River Basin, Weigan River Basin, and Aksu River Basin was extremely low. Additionally, the percentage of the area occupied by annual average vegetation NPP values of greater than 350.00 g C/(m²•a) in the Yarkant River Basin, Hotan River Basin, and Kriya River Basin was extremely low; likewise, the percentage of the area occupied by annual average vegetation NPP values of greater than 350.00 g C/(m²•a) and within 100.00–150.00 g C/(m²•a) in the Tarim River main stream Basin was extremely low. In the desert zone at the edge of the Taklimakan Desert in the Tarim River main stream Basin, annual average vegetation NPP values were all below 150.00 g C/(m²•a), owing to the poor growth conditions there.

3.2.2 General spatial trends of vegetation NPP

The temporal trends of vegetation NPP were calculated for each image element using the Sen slope estimation analysis (Fig. 5a). Vegetation NPP in the Tarim River Basin showed an overall increasing trend. Specifically, vegetation NPP with Sen slope values higher than zero occupied 122,299.75 km² or 87.46% of the total basin, while vegetation NPP with Sen slope values lower than zero occupied 17,535.75 km² or 12.54% of the total basin. Vegetation NPP in other river basins, except for the Tarim River main stream Basin, also showed an overall increasing trend, whereas the Kaikong River Basin, Weigan River Basin, Aksu River Basin, and Kashgar River Basin showed a decreasing trend of vegetation NPP in the intermountain of river origins. The Sen slope estimation results of vegetation NPP change were tested for significance using a combination of the Sen slope estimation and Mann-Kendall tests (Fig. 5b). Overall, vegetation NPP change in 39.67% of the total basin passed the significance testing, whereas vegetation NPP change in 60.33% of the total basin did not.

The area of vegetation NPP with an upward trend that passed the significance test was 54,709.00 km², accounting for 98.63% of the total area that passed, whereas the area of vegetation NPP with a downward trend that passed the significance test was 759.25 km², accounting for the remaining 1.37%. Vegetation NPP change in the Kaikong River Basin, Weigan River Basin, Aksu River Basin, Kashgar River Basin, and Yarkant River Basin, as well as the central areas of the Hotan River Basin passed the significance test and showed an upward trend. Moreover, vegetation NPP change in the Kashgar River Basin and Yarkant River Basin, as well as the central areas of the Hotan River Basin passed the significance test and exhibited a downward trend. Based on the Sen slope calculation of the percentage of the area occupied by different vegetation NPP change rates in the Tarim River Basin (Fig. 5c), we found that the overall trend of vegetation NPP change rate in the basin was increasing. Specifically, the area with vegetation NPP change rate greater than 0.00% was 122,299.75 km², accounting for 87.47% of the total basin area, whereas the area with vegetation NPP change rate lower than 0.00% occupied 17,535.75 km², accounting for 12.53% of the total basin area. At the intersection of the Tarim River main stream Basin, vegetation NPP change rate was lower than 0.00% in the Weigan River Basin, the Tarim River main stream Basin, and the central part of the oasis in the Kashgar River Basin.

3.3 Stability characteristics of vegetation NPP change

The CV results of vegetation NPP change in the Tarim River Basin from 2001 to 2020 were analyzed (Fig. 6). Figure 6a shows that the CVs were in the range of 0.0246–4.4721, with an average of 0.1575. From 2001 to 2020, vegetation NPP in the Tarim River Basin fluctuated little with time and stability, and the spatial variability was not significant (Fig. 6b). The CVs of vegetation NPP change can be divided into four classes, namely very stable, stable, unstable, and very unstable, with area percentages of 20.47%, 61.00%, 12.81%, and 5.71%, respectively. Among them, vegetation NPP was more stable in the intermountain area where the rivers originate from each river basin and the central oasis area, whereas the CVs of vegetation NPP change were larger and vegetation NPP was less stable in the marginal area of the Taklimakan Desert and the oasis-desert ecotone. Vegetation NPP was less stable in the Tarim River main stream Basin, the downstream area of the Yarkant River Basin, and the intermountain area of the Kashgar River Basin.

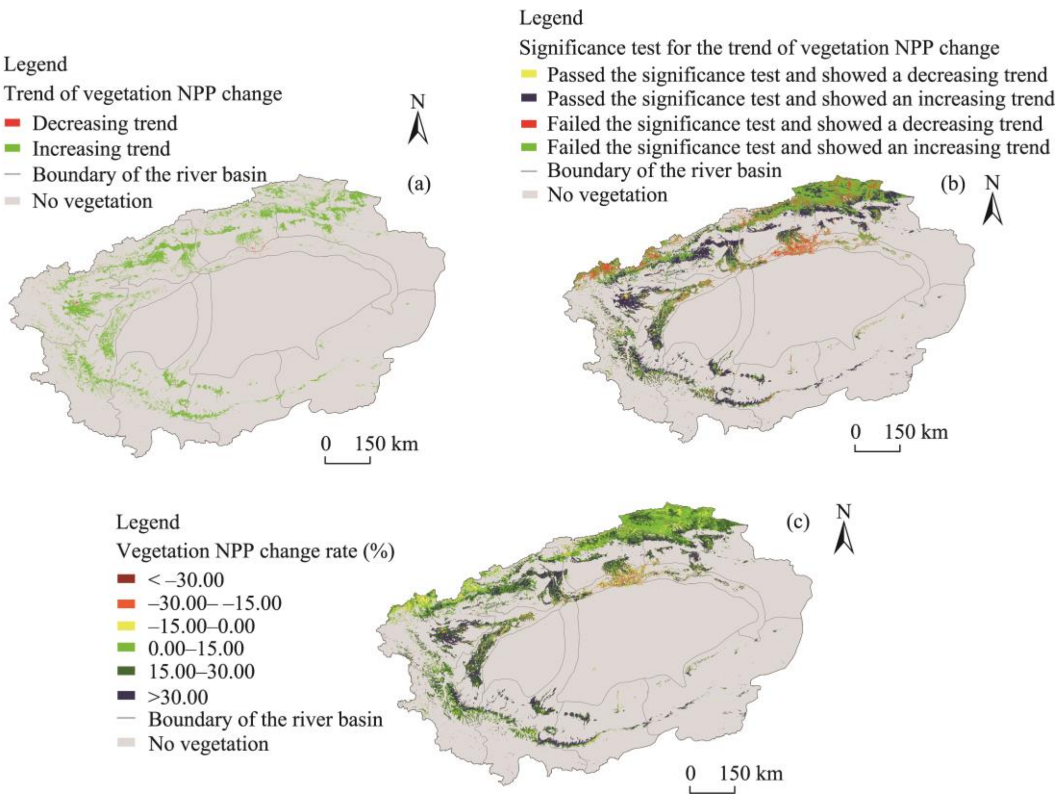

Fig. 5 Spatial distribution of the trend of vegetation NPP change (a), significance test for the trend of vegetation NPP change (b), and vegetation NPP change rate (c) in the Tarim River Basin during 2001–2020

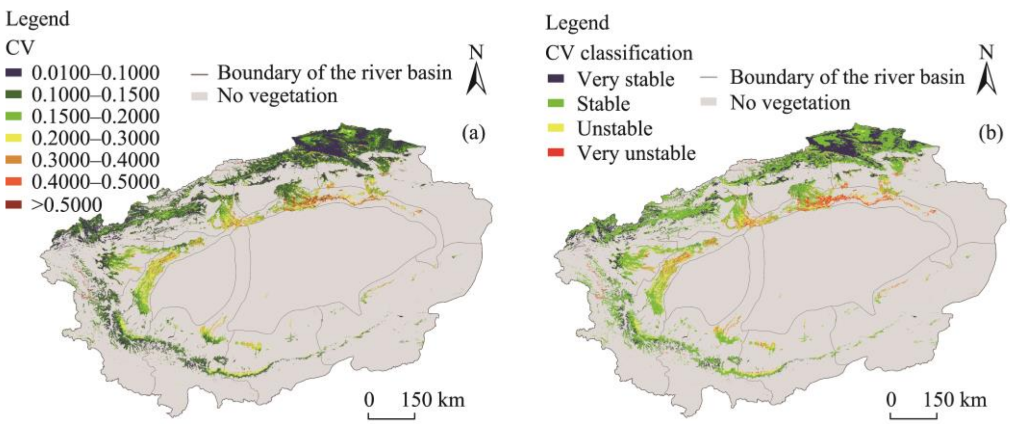

Fig. 6 Spatial distribution of the CV of vegetation NPP change (a) and the classification of the CV of vegetation NPP change (b) in the Tarim River Basin during 2001–2020. CV, coefficient of variation.

3.4 Persistence of vegetation NPP change

This study predominately analyzed the spatiotemporal variation and the stability of vegetation NPP in the Tarim River Basin from 2001 to 2020 and predicted the future variation trend of vegetation NPP by calculating the Hurst index. The anti-continuity of vegetation NPP in the study area from 2001 to 2020 was strong (Fig. 7a), with the Hurst index values in the range of 0.1074–0.9477 (average of 0.4613). Vegetation NPP in the intermountain zone of the Kaikong River Basin, Weigan River Basin, Aksu River Basin, Kashgar River Basin, and Yarkant River

Basin were more sustainable, whereas vegetation NPP in the remaining area was anti-continuity. The predicted future vegetation NPP trend was tested for significance by combining the trend of vegetation NPP change estimated by the Sen slope estimation method (Fig. 7b). The area of future vegetation NPP change with the Hurst index that passed the significance test was 69,304.00 km^2, or 50.26% of the total basin area, whereas the area of future vegetation NPP change with the Hurst index that did not pass the significance test was 68,576.75 km^2, accounting for 49.74% of the total basin area. The results of the future trend of vegetation NPP (indicated by the significance test of the Hurst index) were classified into five categories: increasing-increasing, increasing-decreasing, decreasing-decreasing, decreasing-increasing, and random (Table 1), with the area percentages of 22.18%, 52.59%, 4.57%, 10.98%, and 9.68%, respectively. Thus, the area percentage of vegetation NPP with sustainability characteristic was 26.75%, whereas the area percentage of vegetation NPP with anti-continuity characteristic was 63.57%. The increasing-increasing trend of future vegetation NPP with sustainability characteristic was mainly found in the mountainous areas where the rivers originated in the Kaikong River Basin, Weigan River Basin, and northern Aksu River Basin. This shows that with effective ecological management, the vegetation ecosystem will continue to improve in the future. The decreasing-decreasing trend of future vegetation NPP with sustainability characteristic was primarily found in the mountainous areas where the flows originated in the Kaikong River Basin and Weigan River Basin, the oasis margins, and the northern part of the Kashgar River Basin. This indicates that the ecological restoration of vegetation that has been undertaken in the area is insufficient and that the

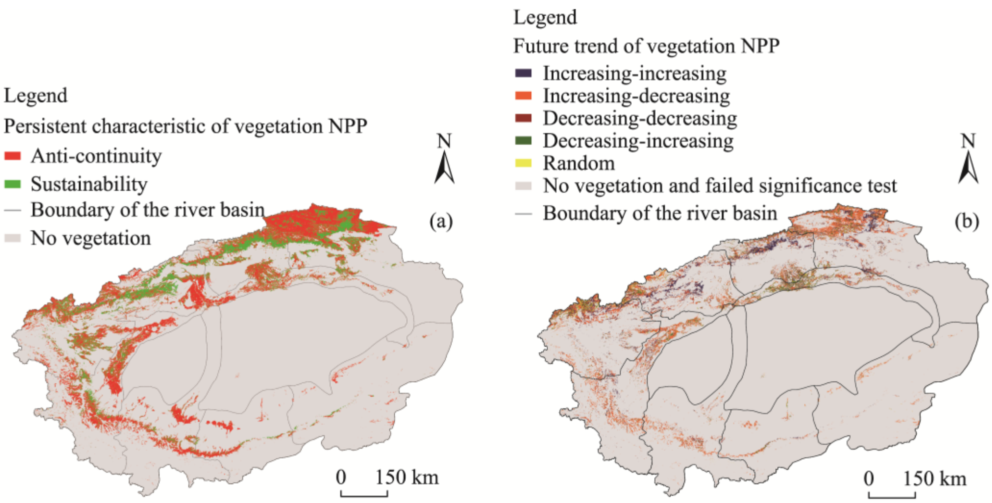

Fig. 7 Spatial distribution of (a) the persistent characteristic of vegetation NPP (indicated by the Hurst index) during 2001–2020 and (b) future trend of vegetation NPP (indicated by the significance test of the Hurst index) in the Tarim River Basin

Table 1 Future trend of vegetation NPP (indicated by the significance test of the Hurst index) in the Tarim River Basin

Sen slope	Hurst index	Future trend	Persistent characteristic
>0	0.0000–0.5000	Increasing-decreasing	Anti-continuity
<0	0.0000–0.5000	Decreasing-increasing	Sustainability
>0	0.5000–1.0000	Increasing-increasing	Sustainability
<0	0.5000–1.0000	Decreasing-decreasing	Anti-continuity
Others		Random	

Note: NPP, net primary productivity.

vegetation ecosystem will continue to deteriorate in the future. Finally, the increasing-decreasing and decreasing-increasing trends of future vegetation NPP with inverse sustainability characteristic were found in all river basins. This also implies that the ecological restoration is insufficient and that the vegetation ecological environment will deteriorate in the future. Vegetation ecological restoration should be enhanced to improve the vegetation ecological environment in the future. The random trend of future vegetation NPP was mainly found in the Kaikong River Basin, Weigan River Basin, Aksu River Basin, and Kashgar River Basin.

3.5 Correlations between vegetation NPP and meteorological factors

3.5.1 Correlation between vegetation NPP and air temperature

Air temperature affects vegetation NPP, and the correlation coefficients and partial correlation coefficients between vegetation NPP and air temperature were calculated (Fig. 8). Figure 8a shows that the correlation coefficients between vegetation NPP and air temperature were in the range from –0.9186 to 0.9180, with an average of 0.0126. The percentage of the area with a positive correlation between vegetation NPP and air temperature was 53.42%, whereas that with a negative correlation between vegetation NPP and air temperature was 46.58%. The partial correlation coefficients between vegetation NPP and air temperature were in the range from –0.9014 to 0.9260, with an average of 0.1033 (Fig. 8b). The percentage of the area with a positive partial correlation between vegetation NPP and air temperature was 62.86% and that with a negative partial correlation between vegetation NPP and air temperature was 37.14%.

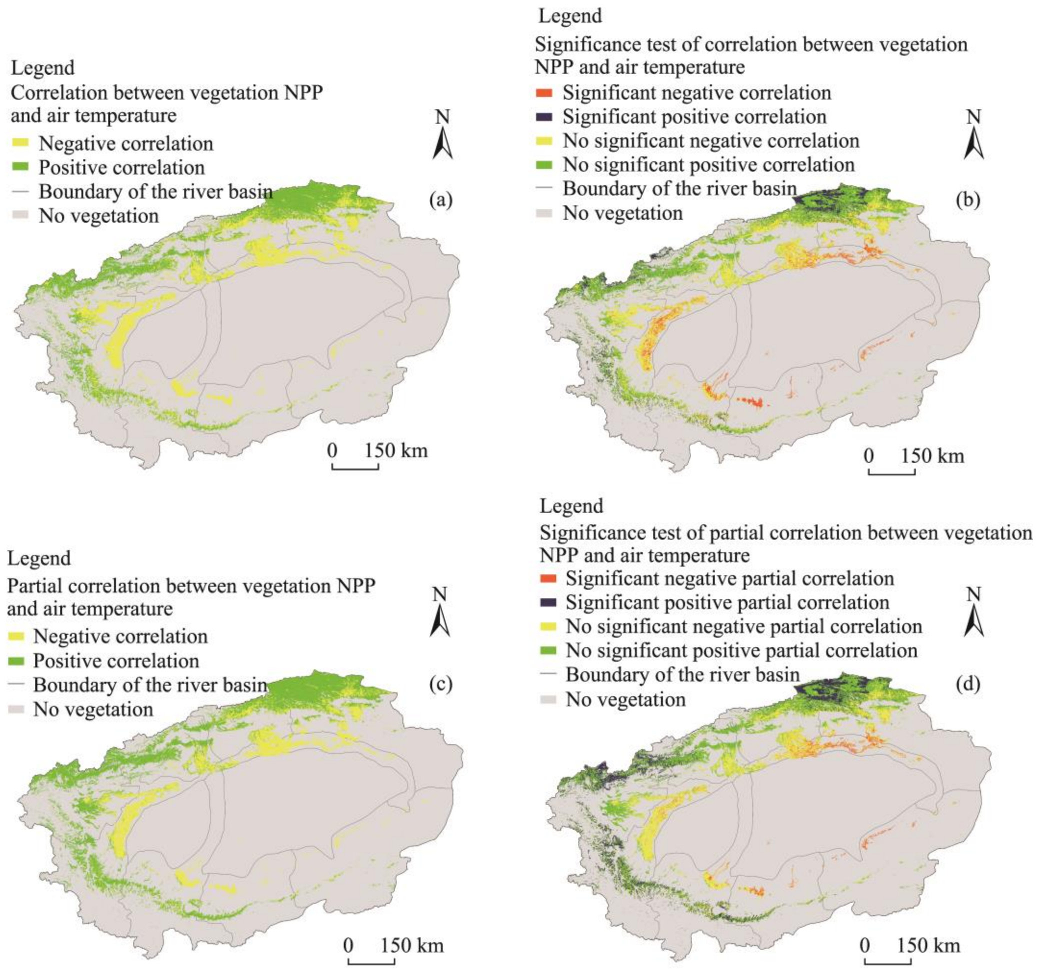

Fig. 8 Spatial distribution of the correlation (a), significance test of correlation (b), partial correlation (c), and significance test of partial correlation (d) between vegetation NPP and air temperature in the Tarim River Basin during 2001–2020

Table 2 lists the significance of the correlation analysis and the significance test between vegetation NPP and meteorological factors. Specifically, 16.77% of the correlation coefficients between vegetation NPP and air temperature passed the significance test; among which, the area where there was a significant positive correlation between vegetation NPP and air temperature occupied 53.74% of the regions that passed the significance test, whereas 46.26% of the regions showed a negative correlation (Fig. 8c; Table 2). Finally, 21.88% of the partial correlation coefficients between vegetation NPP and air temperature passed the significance test; among which, 77.02% of the regions passing the significance test showed significantly positive partial correlation between vegetation NPP and air temperature, whereas 22.98% of the regions exhibited a negative partial correlation (Fig. 8d; Table 2).

Table 2 Significance of the correlation analysis and the significance test between vegetation NPP and meteorological factors

Correlation/Partial correlation	Percentage of the area (%)				
	SPC	SNC	NSPC	NSNC	PST
Correlation between vegetation NPP and air temperature	9.01	7.75	44.41	38.83	16.77
Correlation between vegetation NPP and precipitation	21.32	0.28	64.72	13.68	21.61
Partial correlation between vegetation NPP and air temperature	16.86	5.03	46.00	32.11	21.88
Partial correlation between vegetation NPP and precipitation	25.33	0.28	63.24	11.15	25.61

Note: SPC, significant positive correlation; SNC, significant negative correlation; NSPC, no significant positive correlation; NSNC, no significant negative correlation; PST, passing the significance test.

3.5.2 Correlation between vegetation NPP and precipitation

Precipitation also influences vegetation NPP, and the correlation coefficients and partial correlation coefficients between vegetation NPP and precipitation were calculated (Fig. 9). Figure 9a shows that the correlation coefficients between vegetation NPP and precipitation were in the range from –0.7734 to –0.8703, with an average of 0.2443. The percentage of the area with a positive correlation between vegetation NPP and precipitation was 86.04% and that with a negative correlation was 13.96%. The partial correlation coefficients between vegetation NPP and precipitation were from –0.7876 to 0.9311, with an average of 0.2835 (Fig. 9b). The percentage of the area with a positive partial correlation between vegetation NPP and precipitation was 88.57%, whereas that with a negative partial correlation was 11.43%. About 21.61% of the correlation coefficients between vegetation NPP and precipitation passed the significance test; among which, 98.68% of the regions that passed the significance test showed significant positive correlation between vegetation NPP and precipitation, whereas 1.32% of the regions exhibited a significant negative correlation (Table 2; Fig. 9c). Moreover, 25.61% of the partial correlation coefficients between vegetation NPP and precipitation passed the significance test; among which, 98.91% of the regions that passed the significance test showed significant positive partial correlation between vegetation NPP and precipitation, whereas 1.09% of the regions exhibited a significant negative partial correlation (Table 2; Fig. 9d).

4 Discussion

We conducted this study based on the MODIS NPP dataset from the GEE. The results of the study showed that the annual average value of vegetation NPP in the Tarim River Basin from 2001 to 2020 was 133.35 g C/(m^2•a). In view of the fact that vegetation NPP in the Tarim River Basin mainly focused on the research of grassland NPP, while the study of vegetation NPP in the basin has not yet been undertaken, the results of this study were compared with the mean value of vegetation NPP in the Tarim River Basin. Tong et al. (2019) reported 100.00–150.00 g C/(m^2•a) of vegetation NPP whereas Zhu et al. (2019) reported 110.00 g C/(m^2•a) of vegetation NPP based on the simulation of vegetation NPP and its spatial and temporal patterns in Northwest China. Jiang

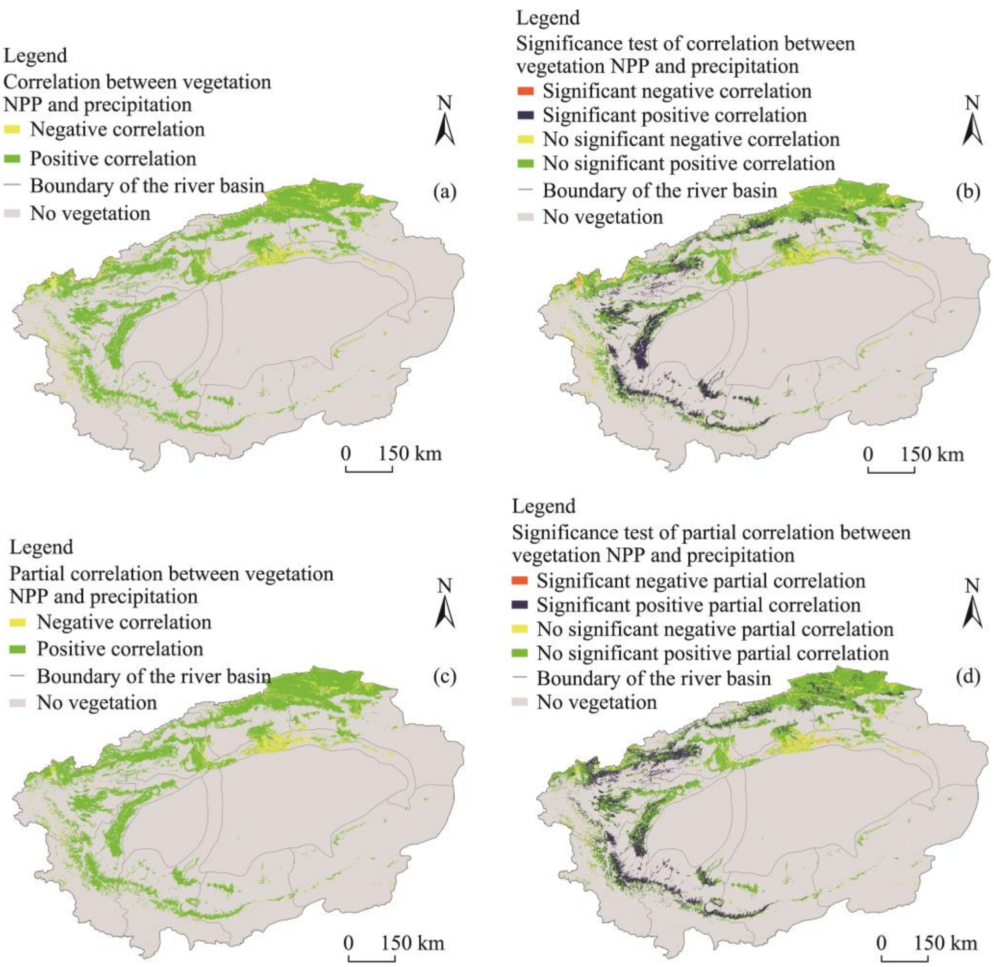

Fig. 9 Spatial distribution of the correlation (a), significance test of correlation (b), partial correlation (c), and significance test of partial correlation (d) between vegetation NPP and precipitation in the Tarim River Basin during 2001–2020

(2021) estimated the annual average vegetation NPP as 120.00 g C/(m^2•a) in the Tarim River Basin, similar with our study.

We analyzed the responses of vegetation NPP to air temperature and precipitation in the Tarim River Basin from 2001 to 2020, calculated the correlation coefficients and partial correlation coefficients of vegetation NPP with air temperature and precipitation, and performed significance tests on the calculated results. The percentages of the area with the positive correlation and partial correlation between vegetation NPP and air temperature and between vegetation NPP and precipitation in the Tarim River Basin were much higher than those with the negative correlation and partial correlation between them. Therefore, in general, vegetation NPP was positively correlated with air temperature and precipitation, that is, vegetation NPP was affected by the joint action of air temperature and precipitation. The area where vegetation NPP was significantly positively correlated with precipitation accounted for 98.68% of the regions that passed the significance test, whereas the area where there was a significant positive correlation between vegetation NPP and air temperature occupied 53.74% of the regions that passed the significance test. Therefore, precipitation is the main climatic factor affecting vegetation NPP in the Tarim River Basin (Zhang et al., 2018; Li, 2019; Tong et al., 2019; Qin et al., 2020; Lan, 2021; Zhang et al., 2021). Moreover, Jiao et al. (2017) showed that, in the Tarim River Basin, the correlation between vegetation NPP and air temperature is not significant enough, which is also consistent with our findings. Mountains, oases, and deserts in arid area constitute a complete complex

system (Deng, 2009), and vegetation NPP in the study area (Tarim River Basin) is mainly concentrated in the mountainous area where the rivers originate, pre-mountainous oasis regions, and margins of the Taklimakan Desert. In the Tarim River Basin, for the area where vegetation NPP and air temperature is positively correlated, the influence of air temperature on vegetation NPP in the intermountain area where the river originates is much higher than that in the oasis and plain areas. Because the mountainous area where the river originates is relatively high above sea level, the differentiation of vegetation presents vertical zonal characteristics, and air temperature changes with the variation of altitude (Jiang et al., 2021). In addition, the analysis of this study shows that vegetation NPP is influenced by the combined effect of two meteorological factors (air temperature and precipitation), of which the effect of precipitation is greater than that of air temperature. Additionally, Figure 8 indicates that air temperature has a higher impact on vegetation NPP in the mountainous area where the rivers originate than in oasis and plain areas. Moreover, Figure 9 shows that the overall vegetation NPP in the Tarim River Basin is more influenced by precipitation.

The average annual vegetation NPP in the Tarim River Basin from 2001 to 2020 showed an upward fluctuating trend. Owing to the highly fragile ecological environment in the basin, the government has implemented policies such as forest closure and reforestation to protect areas with relatively intact ecology and restore damaged areas, improving ecological environment, vegetation cover, and growth conditions (Xiong, 2018). Therefore, vegetation NPP in the Tarim River Basin has been showing a positive trend over time. Vegetation NPP in the Tarim River Basin is higher in the intermountain and pre-mountain alluvial areas where the rivers originate, and lower in the marginal areas of the Taklimakan Desert and the southern marginal areas of the Tarim River Basin, where grasslands, meadows, coniferous forests, and other vegetation types are predominantly distributed in the intermountain areas. These areas generally have higher levels of vegetation cover and vegetation NPP. In the pre-mountain alluvial areas (including the oasis area with fertile soils), vegetation cover is higher, and vegetation NPP increases during the growing season. The marginal zone of the Taklimakan Desert is characterized by poor water resources and vegetation growth environment, as well as low soil fertility. Only some plants can grow on sandy soils, resulting in low vegetation cover and vegetation NPP. The southern edge of the study area is dominated by high mountains covered with snow throughout the year. There is no vegetation growing on the mountain summits, leading to low vegetation NPP. The results of the Sen trend of vegetation NPP in the Tarim River Basin showed that the overall vegetation NPP in the basin is increasing. Owing to the implementation of fallowing and forestry ecological construction projects in the basin, by the end of 2019, 230.12 km^2 of the area had been fallow and protected in the middle and upper reaches of the Tarim River, 667.00 km^2 of poplar and shrub forests have been planted in the upper reaches, and 66.70 km^2 of desert forests have been restored in the lower reaches (Merchant, 2021). The implementation and promotion of various ecological construction projects in the basin have led to the expansion of vegetation cover and an overall upward trend of vegetation NPP. The high vegetation NPP in the marginal zone of the Taklimakan Desert and the oasis-desert ecotone indicate that the degradation degree of vegetation ecosystem in these regions is high, and vegetation protection should be strengthened.

The change in vegetation NPP in the Tarim River Basin showed the characteristic of anti-continuity, mainly because the Tarim River Basin is an ecologically damaged area with human interference (Xiong, 2018). Under the current situation of climate warming, the inflow of water from the source area has increased, although the amount of water supplied by the source to the main channel has not substantially increased. Even when the basin is in a high-water period, the current situation of environmental deterioration in the main channel cannot be alleviated. Owing to the lack of an effective unified management system, the use of water resources in the basin is relatively low. Although emergency water diversion projects have been implemented in the Tarim River Basin, such projects can only alleviate temporary problems in the long run. The destruction of the ecological environment remains a serious challenge facing the Tarim River Basin (Ye et al., 2006).

5 Conclusions

The ecological environment in the Tarim River Basin is fragile, and the vegetation growth status is of great concern. A detailed analysis of vegetation NPP in the Tarim River Basin is important for promoting sustainable development within the region. This study analyzed the spatiotemporal variation in vegetation NPP in the Tarim River Basin from 2001 to 2020 based on the GEE, using vegetation NPP data and available meteorological data, combining the Sen slope estimation method, stability coefficient, and rescaled range analysis method. Correlation analyses were used to determine the correlations between vegetation NPP and meteorological factors, namely air temperature and precipitation. Overall, vegetation NPP in the Tarim River Basin showed a fluctuating upward trend, spatially characterized by a decrease from northwest to southeast along the outer edge of the study area. The maximum vegetation NPP value appeared in the Kashgar River Basin, with a value of 589.64 g C/(m^2•a). The mean stability coefficient (CV) was 0.1575, the mean Hurst index obtained from the simulation of future vegetation NPP change was 0.4613, the area with anti-continuity characteristic accounted for 63.57% of the total basin, and the future change trend of vegetation NPP was dominated by anti-continuity characteristic. Among the correlation coefficients of vegetation NPP with air temperature and precipitation, the area with a significant positive correlation between vegetation NPP and air temperature accounted for 53.74% of the regions that passed the significance test, while the area with a significant positive correlation between vegetation NPP and precipitation occupied 98.68% of the regions that passed the significance test. Precipitation was significantly positively correlated with vegetation NPP, whereas the correlation between vegetation NPP and air temperature was not significant. The resolution of vegetation NPP in this study was low, and there was an issue of mixed pixels. In addition, we only selected the main meteorological factors to discuss the impact on vegetation NPP, and the selected influencing factors were relatively single. Therefore, we recommend considering multiple influencing factors of vegetation NPP under different scenarios in future research.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (42161049, 41761019, 41061052) and the Special Project for Talent Development in the Western Region (201408655089). We acknowledge the editors and anonymous reviewers for their helpful comments on the improvement of this manuscript.

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